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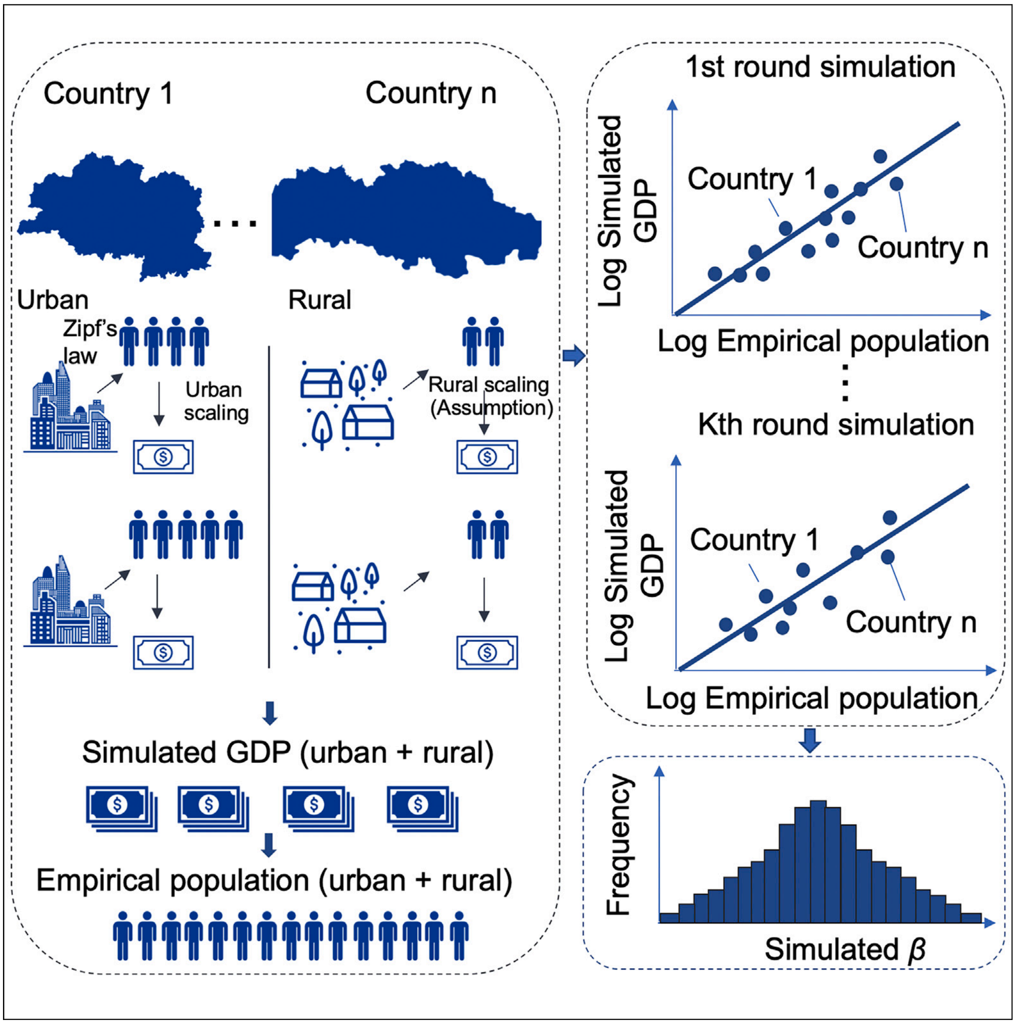

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Highlights

Sub-linear scaling between national population and development performance is identified

A theoretical framework is established to explore the origin of scaling in countries

Urbanization plays a pivotal role in transforming national development

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Scaling of development indicators in countries and its origin

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SUMMARY

Population-normalized indicators (e.g., GDP per capita), under the assumption of the indicators scaling linearly with population, are ubiquitously used in national development performance comparison. This assumption, however, is not valid because it may ignore agglomeration effect resulting from nonlinear interactions in socioeconomic systems. Here, we present extensive empirical evidence showing the sub-linear scaling rather than the presumed linear scaling between population and multiple indicators of national development performance. We then develop a theoretical framework based on the scaling rule observed in cities to explore the origin of scaling in countries. Finally, we demonstrate that urbanization plays a pivotal role in transforming national development from limited sub-linear growth to unlimited super-linear growth. This underscores the significance of urbanization in achieving sustained growth and elevating human living standards at the national level. Our findings have the potential to inform policies aimed at promoting equitable inter-country comparison and achieving sustainable development in countries.

INTRODUCTION

Achieving sustained growth for countries while operating within the planetary boundary is a critical aspect of fulfilling the United Nations Sustainable Development Goals.[1] Measuring the progress of country development involves assessing a diverse range of economic, social, and environmental indicators. Many of these indicators, which reflect the magnitude of development performance within a country (e.g., gross domestic product [GDP]), are commonly normalized by population (e.g., GDP per capita) to facilitate meaningful comparisons among different countries.[2–15] Despite its widespread use, the appropriateness of employing population-normalized indicators for such comparisons has been a subject of prolonged debate.[16–21] The foundation of this comparison method lies in the assumption that these indicators exhibit linear scaling with population size.[18,22] For an equitable and accurate inter-country comparison, it becomes imperative to critically investigate the validity of this underlying assumption.

Previous research has extensively delved into the impact of population size on various facets of human development within urban systems, including economic output,[23–25] individual needs,[26–28] innovation,[29,30] natural resources,[19,31,32] contagious diseases,[33] climate change,[34–36] land expansion,[37–39] and crime and accident.[40] Literature reveals that many development indicators can be determined by the ubiquitous scaling law at the city level, represented by the equation $Y=Y_0N^{\beta}$, where Y is an development indicator, Y_0 is its baseline of the indicator, N is city population size, and β is the scale-invariant elasticity indicating the percentage change in Y following a 1% increase in N.[41–43] Extensive research has found empirical evidence of super-linear scaling ($\beta \approx 1.15$) of a wide range of socioeconomic-related indicators (e.g., GDP, wages, number of bank deposits, and crimes) at the city level.[18,23,28,44] Additionally, to elucidate the super-linear scaling observed in urban systems, Bettencourt[45] developed a quantitative theoretical framework to explore the origin considering various key parameters, such as local social interaction, occupied space, and transportation cost. The research by Bettencourt et al.[44] further proposed that, unlike the limited growth pattern driven by sub-linear scaling ($\beta \approx 0.75$) in biological organisms, super-linear scaling ($\beta \approx 1.15$) in urban system has the potential to achieve sustained growth pattern with successive shorter periods of super-linear innovation reset. Besides the plenty of urban population-based scaling investigation, a few studies also investigated other urban properties, such as GDP[46] and distance.[47,48] While there has been extensive exploration of scaling dynamics at the city level, which are pivotal constituents of countries, to our knowledge, few of the studies have investigated the scaling effect of population on development indicators at the country level. Considering the prevalent use of population-normalized indicators in inter-country comparisons, it becomes imperative to ascertain whether national development indicators exhibit

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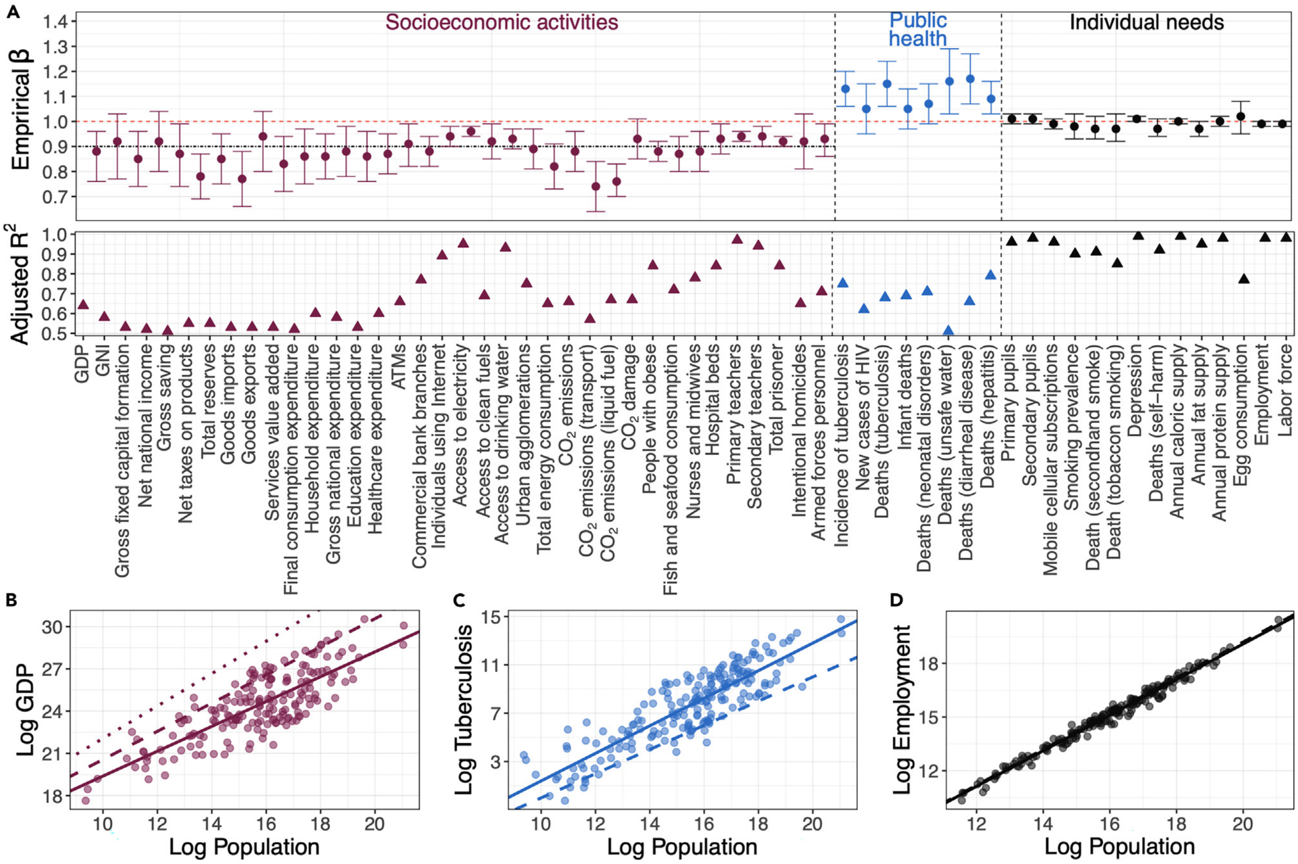

Figure 1. Empirical scaling results

(A) Empirical scaling exponents with 90% confidence interval for country-level indicators of socioeconomic activities, public health, and individual needs. Dot-dash line shows the approximate scaling exponent (β = 0.9) for most socioeconomic activity indicators, and dash line shows the linear scaling (β = 1). Examples of scaling relationships in countries for GDP (B), incidence from tuberculosis (C), and employment (D) in 2019; solid line shows the best-fit relation, dash line shows the linear scaling, and dotted line shows the scaling of the same indicator in cities.

a linear scaling relationship with population. This examination holds significant implications for understanding the broader patterns of socioeconomic development across different countries and regions.

In this study, our primary goal is to examine the scaling of various indicators of national development across the dimensions of socioeconomic activities, public health, and individual needs. We uncover substantial empirical evidence suggesting that multiple key national development indicators generally follow scaling functions relative to population size, which are consistent across countries over time. Building upon these empirical findings, we develop a quantitative theoretical framework based on the scaling laws observed in cities to delve into the origin of country-level scaling. Furthermore, our investigation extends to analyzing the growth patterns within nations and explore the possibilities of transitioning to sustained growth in cities through urbanization. Through our examination of the scaling of development indicators for countries, coupled with the initial exploration of its origin and growth patterns, our study has the potential to contribute to a novel approach of comparing the development performance of nations. Our findings on growth dynamics within countries also lay the groundwork for the formulation of effective strategies aimed at accomplishing global sustainable development goals.

RESULTS

Empirical scaling at the country level

By analyzing data of 213 countries and regions (Table S1) from 1995 to 2019,[49–51] we find many important development indicators scale with population universally (adj-R^2 > 0.5, Figure 1; Table S2).

Specifically, we find indicators of socioeconomic activities scale sub-linearly (β < 1) with population, implying the growth rate of these indicators declines as population increases. Consequently, the assumption behind classical per capita socioeconomic indicator-based national comparisons is invalid, as these indicators do not exhibit linear scaling with population. Moreover, the sub-linear scaling suggests a restricted growth potential. Conversely, super-linear scaling implies an unlimited growth potential (see section 2.3 for more details). Some of these indicators represent socioeconomic welfare such as GDP, net national income, healthcare expenditure and resources, and access to safe

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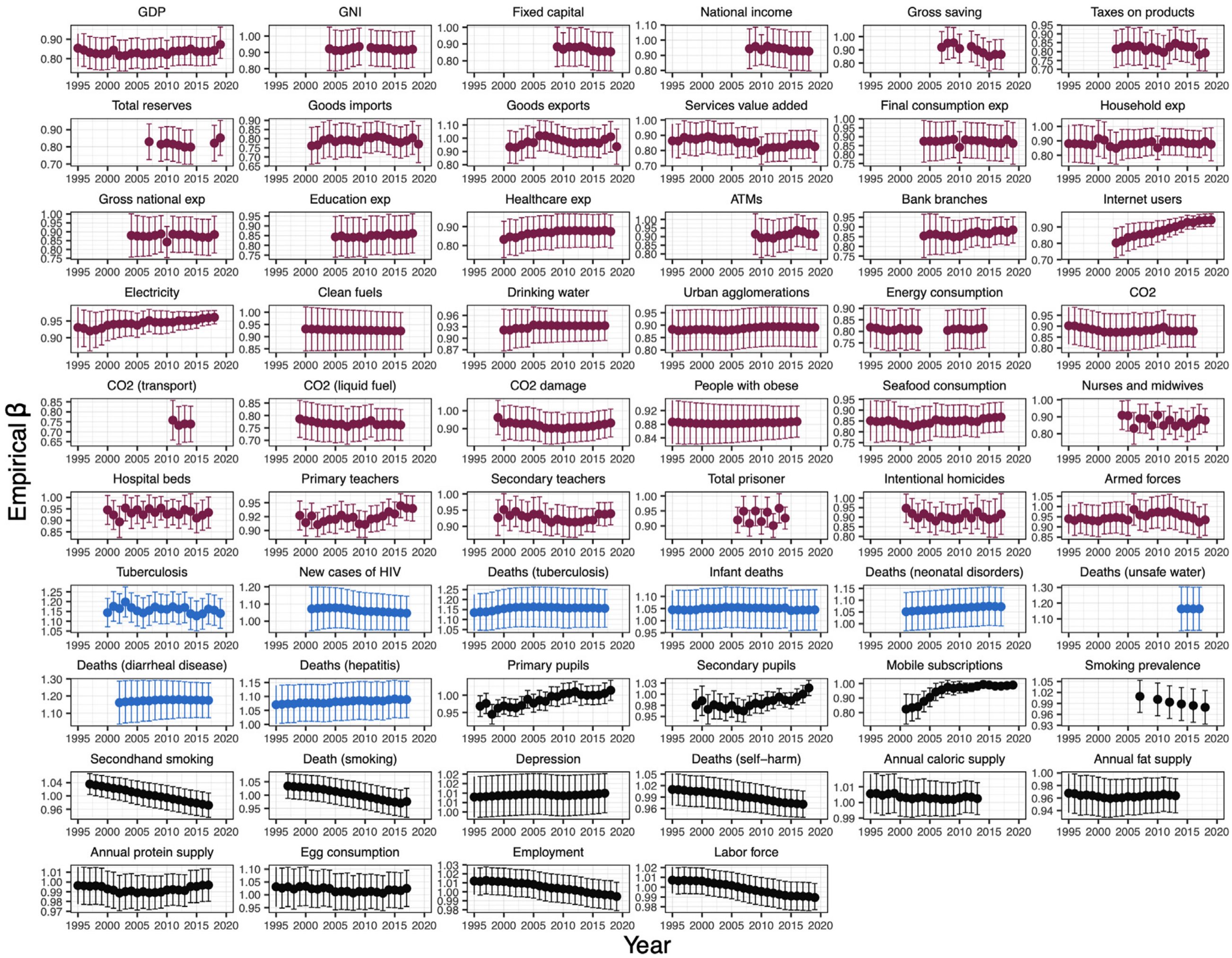

Figure 2. Scaling exponents with 90% confidence interval in each year for indicators of socioeconomic activities, public health, and individual needs (only exponents with adj-R^2 > 0.5 are shown)

drinking water and electricity; thus sub-linear scaling indicates compromised welfare for each individual with increased population. In contrast, higher value of indicators such as CO_2 emissions, energy consumption, and number of prisoners are less desired; thus sub-linear scaling reflects higher per-capita efficiency with larger population. These results are different from what was found for cities in which similar indicators scale super-linearly with urban population ($\beta \approx 1.15$).[18,25,28,42,44,45,52–55]

Our results also show indicators related to public health scale super-linearly with population ($\beta_p \approx 1.1$), such as infant death, death from hepatitis, and incidence of tuberculosis. This suggests that the performance of public health tends to decline for individuals with increased population in a country. The super-linear scaling of public health indicators may be explained by the sub-linear scaling of the socioeconomic activity indicators related to healthcare, such as healthcare expenditure, number of nurses and midwives, and number of hospital beds ($\beta_h \approx 0.9$). Specifically, the number of death or disease $Y_p = Nf$ where f is the per-capita death or disease in a country which is proportionate to the inverse of per-capita access to healthcare ($Y_h/N = Y_{h0}N^{\beta_h}/N = Y_{h0}N^{\beta_h - 1}$); thus $Y_p = Nf \sim N/(Y_h/N) \sim N^{2-\beta_h}$ where the exponent $\beta_p = 2 - \beta_h \approx 1.1$.

We also find indicators of individual needs scale linearly with population in countries, which has also been observed in cities.[28,44] This indicates that, on average, individuals in different countries tend to have the same level of demand related to these indicators, regardless of the size of population. The fact that individual need indicators scale linearly in both countries and cities can be explained by that the terminal units of socioeconomic networks in both countries and cities are the same—individuals—and their size is invariant.[53]

The exponents of most indicators are consistent across different years (Figure 2), indicating the scaling of these indicators could be the result of some fundamental mechanisms governing the socioeconomic dynamics of countries. However, it is worth noting that a few indicators, such as mobile subscriptions and internet users, display continuously growing or declining exponents. This behavior can be attributed to the fact that the penetration rate of these basic services tends to increase gradually until it reaches 100% (i.e., achieving the same per capita

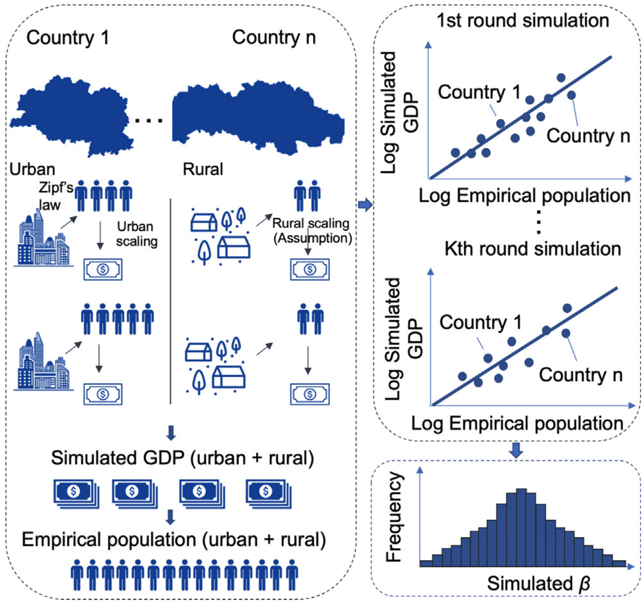

Figure 3. Processes estimating the scaling exponent of socioeconomic activity indicators (e.g., GDP) for countries

value across countries) as the economy grows. As a result, the scaling of these indicators, particularly those related to basic services, is expected to eventually become linear due to this convergence.

A theoretical framework for exploring scaling at the country level

Socioeconomic activity indicators exhibit different scaling patterns between countries and cities: sub-linear scaling is observed in countries, as revealed by our study, while preceding studies have shown super-linear scaling in cities. This implies aggregation effects exist in cities from the concentration of population[44,54] but do not exist in countries with population increase. Given that a country is an ensemble of urban and rural areas, we propose a theory to explore the origin of scaling of development indicators in countries based on the scaling law observed in cities.

To understand the scaling exponent of development indicators among countries, we need to estimate the value of the development indicator for each country given its population size. A country is an ensemble of urban and rural areas; thus the total level of a development indicator of a given country is the sum of its urban and rural levels, which in turn are the sum of the levels of each urban and rural area, respectively. This can be written as $Y_{total} = Y_{urban} + Y_{rural} = Y_0 \sum_i N_{u,i}^{\beta_u} + \alpha Y_0 \sum_j N_{r,j}^{\beta_r}$, where Y_0 is the common economic base of all urban areas in the same country which differs across countries, $N_{u,i}$ is the population size of city i, the scaling exponent β_u is from urban scaling literature (β_u = 1.15 for socioeconomic activity indicators and $\beta_u = 1$ for individual need indicators), αY_0 is the common economic base of all rural areas for the country assumed to be proportional to the urban economic base Y_0, α is the ratio between rural and urban economic base of this country and differs across countries, $N_{r,j}$ is the population size of rural area j. In addition, the value of the scaling exponent β_r for rural area is unknown from the current literature. Given the relative low population density and size in a given rural area compared with that in a city, rural area are considered with no or very limited aggregation effect and are not significantly distinct from one another. Specifically, we assume linear relationship between the rural portion of Y (Y_{rural}) and rural population, which means $\beta_r = 1$ for any development indicator. Thus $Y_{total} = Y_{urban} + Y_{rural} = Y_0 \sum_i N_{u,i}^{\beta_u} + \alpha Y_0 \sum_j N_{r,j}^{\beta_r} = Y_0 \sum_i N_{u,i}^{\beta_u} + \alpha Y_0 N_r^1$, where N_r is the total rural population of the country.[49] Y_{urban} and Y_{rural} of a country can then be estimated once Y_0, α, and the distribution of urban population (i.e., population for each urban area) are given. We also test several ranges of β_r and find varying β_r does not affect the results and conclusions to be discussed in the further text (Figure S1).

Estimating Y_0 for a given country requires empirical data on the urban portion of Y_0 and urban population for all cities. However, such data may not always be readily accessible for all indicators across all countries. Despite this challenge, extensive research has consistently demonstrated that population serves as a robust predictor with high explanatory power (indicated by high R^2) in regression models for urban development indicators. This suggests that in a given country, most cities align closely with the regression line derived from such data. Consequently, estimating Y_0 for a country using pairwise empirical data on urban development indicators and population from various countries yields estimates that closely resemble those derived from empirical data encompassing all cities within that country. To enhance precision and mitigate uncertainty, we adopt a strategy wherein Y_0 is calculated for each city by gathering empirical data. This approach allows for the derivation of a range of Y_0 values for countries, rather than a single specific value, thereby offering a more comprehensive understanding of the underlying dynamics.

Take GDP as an example of socioeconomic activity indicators (Figure 3). We collect the pairwise empirical data on urban GDP and population of almost 900 cities from 150 countries and regions.[56] We calculate Y_0 for each city using $Y_0 = GDP_{urban}/N_{urban}^{1.15\pm\delta}$, where GDP_{urban} is the

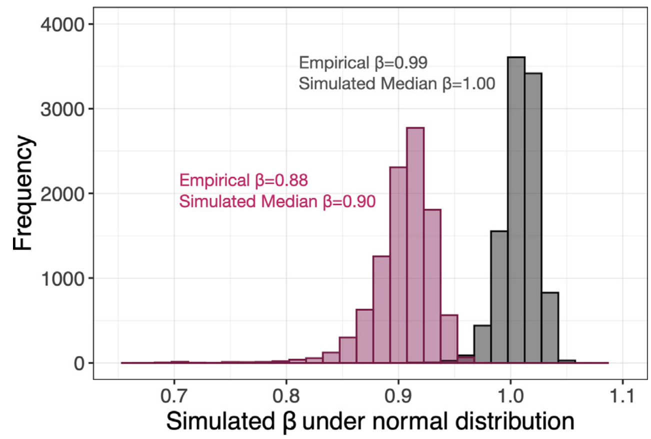

Figure 4. Histogram of β for GDP (socioeconomic activity, red) and employment (individual need, gray) in countries from 10,000 simulations with normal distribution of parameters

Uniform distribution generates similar results (Figure S3).

GDP of the city, N_{urban} is the population of the city, and δ represents the uncertainty of the estimation. Previous studies show that the scaling exponent of the GDP in urban systems ranges between 1.1 and 1.2,[28,45] indicating δ to be 0.05. We then estimate the range of Y_0 for each country by assuming it varies between the minimal and maximum values of the Y_0 of its cities.

We use the Zipf's law to approximate the distribution of urban population (population size for each urban area) among cities in a country. Zipf's law implies that the city in any country with the largest population is generally twice as large as the next largest, and so on.[57,58] This could be formularized as $N_{u,i} = N_1 i^{-1}$, where $N_{u,i}$ is the population of a city i, i is the rank of the population size of the city, and N_1 is the population size of the largest city. However, many empirical studies found that Zipf's exponent can vary around 1 depending on the country, the time period, the definition of cities, and the fitting method.[57,58] We extend the Zipf's law function as $N_{u,i} = N_1 i^{-(1 \pm \zeta)}$ to consider the uncertainty of the approximated distribution of urban population. Empirical studies show that most of the Zipf's exponents vary between -0.7 and -1.3,[59,60] which helps us set ζ as 0.3. We collect empirical urban population data for almost 1,900 cities with more than 300,000 people from 150 countries and regions from the Department of Economic and Social Affairs of United Nations.[61] Given the total urban population and the population of the largest city for each country are known, we only need to estimate the urban population less than 300,000 using the extended Zipf's law. Notably, approximately 59% of the urban population size data for each nation in our study are based on empirical evidence, minimizing reliance on simulated data alone (Figure S2). For instance, in the case of China, where there were around 0.7 billion urban population in 2015, the UN data covered approximately 0.5 billion people from the top 424 cities. Consequently, only about 30% of the urban population of small cities in China was simulated in our study, which had an insignificant impact on our scaling results.

Next, we run simulations to test the theory. We vary α within the range [0.7, 1.3] to consider the uncertainty of the simulated rural GDP. It is important to note that α serves as a parameter utilized to distinguish the outputs in the rural and urban systems. For each simulation, we randomly and independently select a value for each parameter within the parameter interval for each country. After randomly simulating the GDP for each country, we conduct the regression to find the simulated β. We repeat the simulation for 10,000 times. Note that the parameter randomization follows a uniform distribution, such as $Y_0 \sim U(min(Y_0), max(Y_0))$, $\delta \sim U(-0.05, 0.05)$, $\zeta \sim U(-0.3, 0.3)$, and $\alpha \sim U(0.7, 1.3)$. We also consider normal distribution for these parameters, such as $Y_0 \sim N((max(Y_0) - min(Y_0))/2 + min(Y_0), (max(Y_0) - min(Y_0))/6)$, $\delta \sim N(0, 0.05/3)$, $\zeta \sim N(0, 0.3/3)$, and $\alpha \sim N(1, 0.3/3)$.

Take employment as an example of individual need indicators. We collect pairwise empirical data on urban employment and population of almost 900 cities from 150 countries and regions.[56] We calculate Y_0 for each city using $Y_0 = Employment_{urban}/N_{urban}^{1 \pm \delta}$, where $Employment_{urban}$ is the employment of the city and N_{urban} is the population of the city. The scaling exponent of the employment in urban systems is found to range between 0.98 and 1.02,[44] indicating $\delta = 0.02$. Similarly, we simulate the β of employment using the parameters under uniform and normal distributions, respectively. Please note that we do not simulate the super-linear scaling of public health indicators, as it can be fully explained by the sub-linear scaling of socioeconomic indicators such as "health expenditure", coupled with the unavailability of relevant empirical data.

Our results show that the simulated samples derive similar scaling exponents from the empirical observations (Figure 4). Specifically, the median of the simulated β for GDP (socioeconomic activity) and employment (individual need) are close to those from empirical data (0.90 vs. 0.88 and 1.00 vs. 0.99, respectively).

Continuous growth of nations

Previous studies found that there are three patterns of population growth based the scaling exponent.[44,53] As shown in the Figure 3 by Bettencourt L.M. et al.,[44] $\beta < 1$ leads to a sigmoid growth, and population growth ceases in long term as it reaches a finite carrying capacity.

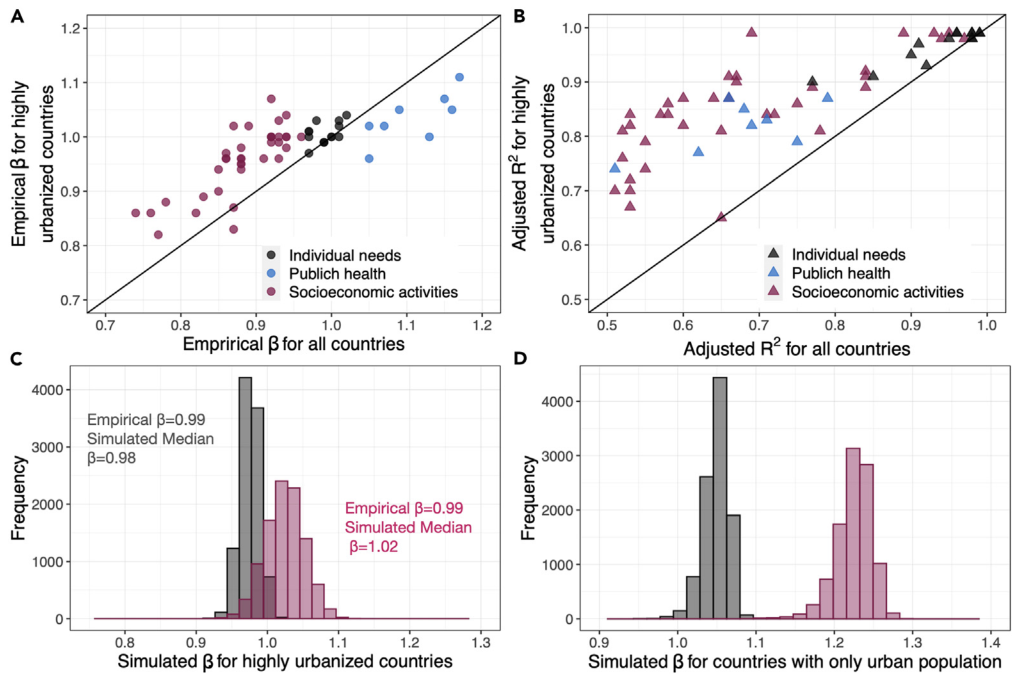

Figure 5. Comparison of empirical scaling exponents

(A) and adjusted R^2 (B) of development indicators between highly urbanized countries and all countries. Histogram of simulated β for GDP as an example of socioeconomic activity indicators (red) and employment as an example of individual need indicators (gray) for highly urbanized countries (C) and for all countries with only urban population (D) from 10,000 simulations. Distributions of parameters in (C) and (D) are normal, and uniform distribution generates similar results (Figure S5).

Similar patterns are found in biological systems and companies where the organism ultimately dies[53,62] and the company demises.[63] When $\beta = 1$, it leads to an exponential population growth, while $\beta > 1$ leads to a growth which is faster than exponential growth and scaling diverges within a finite time and collapses due to limited resource. This means cities are destined to eventually stopping growing.[44] However, this collapse could be avoided by innovation and technology advances to reset the initial conditions (Figure 4 by Bettencourt L.M.[44]). In that case, a new cycle is initiated, and cities continue to grow. The reset process could be continually repeated and lead to multiple growth cycles. The side effect of this reset is the time to collapse in the following cycle becomes shorter, which means major innovations must arise at an accelerated rate.[44,53]

Our results show that countries are more like biological systems and companies rather than cities, in which development outcomes grow sub-linearly with population. This indicates countries will eventually stop growing or even collapse. How can countries sustain continued growth, or is it even possible? Urbanization might be the solution, because, theoretically, cities grow super-linearly and their growth can be sustained.[44]

To test this hypothesis, we examine 58 highly urbanized countries (urbanization rate in 2019 > 80%) (Table S3; Figure S4). We show that the scaling exponents of most socioeconomic activity indicators increase from around 0.9 (sub-linear scaling, Figure 5A) to close to 1 (linear scaling, Figure 5A). The scaling of individual need indicators is still linear for these highly urbanized countries (Table S4). In addition, the values of Adj-R^2 for most indicators are improved, meaning population can better explain the variations of these indicators when countries become more urbanized (Figure 5B). We also simulate β for GDP as an example of socioeconomic activity indicators and employment as an example for individual need indicators for these highly urbanized countries. Results show that the simulated β are very close to the empirical observations (Figure 5C), 1.02 vs. 0.99 for GDP and 0.97 vs. 0.99 for employment. These results indicate urbanization can potentially help countries grow with increased scaling exponents from sub-linear to linear. However, is it possible for countries to grow super-linearly?

If each country is a city (e.g., Singapore), the scaling of countries will be super-linear, leading to open-ended growth. But what if each country is fully urbanized but with multiple cities? We test the scaling of the development indicators of countries as if each country only has its major cities for which empirical data are available (900 global cities).[56] We find the scaling of national socioeconomic activity indicators would become super-linear ($\beta \approx 1.06$) (Figure S6A), while that of individual need indicators would remain linear ($\beta \approx 1.00$) (Figure S6B). Moreover, assuming each country only has its current urban population, we also find that the simulated β for GDP as an example of socioeconomic activity indicators would be around 1.2, while that of employment as an example of individual need indicators would still be around 1.00 (Figure 5D). Both scenarios indicate that urbanization can shift the scaling of socioeconomic indicators for countries to super-linear. Indeed, urbanization is generally expected to promote economic growth as it releases the agricultural labor into industry- and service-based economies,[64] and the aggregated population in cities increases the social interactions and balance benefits and costs in a way that leads to super-linear growth for socioeconomic properties.[45,65] However, super-linear growth also comes with super-linear increases of undesired socioeconomic outcomes (e.g., crime and resource consumption).[44] This calls for policy attentions to these accompanying but undesired consequences of urbanization.

DISCUSSION

Despite the high diversity and complexity across countries, our findings suggest they follow common scaling relationships with population size, which sheds light on addressing the challenge of maintaining sustained growth within our planetary boundary. In addition, we also examine the outsized role of a few nations with the model. Specifically, we test the impact of top developing and less developed nations with large populations on the scaling exponents of each kind of indicator under various scenarios (Method). Results show that scaling relationships do not change too much even if we remove these few outsized countries or double or halve the indicator performance (Figure S7). We also validate that these relationships are relative consistent across different years (Figure 2) and not very sensitive to research samples (Figure S8). In addition, our research reveals that the scaling in countries is largely driven by the scaling in cities and super-linear growth in countries is largely due to urbanization. The variance in scaling between urban and national systems may stem from rural areas. In rural settings, the scaling tends to approximate a linear or sub-linear trend, owing to their comparatively lower population density and size when contrasted with cities. By viewing countries as a structure that include an ensemble of self-similar cities and rural areas, we find these systems are governed by universal mechanisms regardless of social, economic, political, cultural, and geographical variabilities.

These findings provide a quantitative and mechanistic understanding of development and growth at the country level. A critical implication for development is that, by keeping other factors constant, if a country could concentrate people and resources in megacities, its development indicators have potential to improve significantly. We propose two potential strategies to achieve this. The first strategy is to continue the urbanization process to let the super-linear scaling effect existing in the urban system dominates national development. We take GDP as an example. The total GDP of a given country is the sum of its total urban and rural GDP, which can be expressed as $Y = \sum_{i=1}^{n} Y_0 \times N_i^{1.15 \pm \delta} + \sum_{l=1}^{m} \alpha_0 \times Y_0 \times N_{rural}^1$. This is because $Y_{urban} > Y$ given $Y_{urban} = \sum_{i=1}^{n-1} Y_0 \times N_i^{1.15 \pm \delta} + Y_0 \times (N_n + \Delta N)^{1.15 \pm \delta} + \sum_{l=1}^{m} \alpha_0 \times Y_0 \times (N_{rural} - \Delta N)^1$, where ΔN is the size of rural population moving to the city with the least population (N_n). This also holds if the rural population (ΔN) moves to any city. The second strategy is to concentrate urban population given the constant urban population and rural population. We propose two specific ways to achieve it. The first way is that the country can have fewer but larger cities. This is because $Y_{less} > Y$ given $Y_{less} = \sum_{i=1}^{n-2} Y_0 \times N_i^{1.15 \pm \delta} + Y_0 \times (N_{n-1} + N_n)^{1.15 \pm \delta} + \sum_{l=1}^{m} \alpha_0 \times Y_0 \times (N_{rural}^1)$, where N_n is the size of population of the smallest city. This also holds if any two cities merge as one. The extreme case is the country only has one city. Having fewer but larger cities might not be feasible for all countries. An equivalently effective approach is to better connect cities with better infrastructure such as high-speed rail and the Internet. The second way is that the country can encourage mega cities to concentrate its urban population. This because $Y_{mega} > Y$ given $Y_{mega} = \sum_{i=2}^{n-1} Y_0 \times N_i^{1.15 \pm \delta} + Y_0 \times (N_1 + \Delta N)^{1.15 \pm \delta} + Y_0 \times (N_n - \Delta N)^{1.15 \pm \delta} + \sum_{l=1}^{m} \alpha_0 \times Y_0 \times (N_{rural}^1)$, where N_1 is the size of population of the largest city and ΔN is the size of population moving from the smallest city to the largest city. This also holds if ΔN is from a smaller city to a larger city. The extreme case is that the country has one mega city and the rest of the urban population is allocated in extremely small cities. A more practical scenario is to have multiple megacities to host the majority of urban population. The main difference between the two strategies lies in the focus on rural population movement. For the first strategy, the emphasis is on encouraging rural population to migrate to cities, regardless of the size of the city, in order to increase the overall urbanization rate. This approach aims to leverage the super-linear scaling effect inherent in urban systems to drive national development. In contrast, the second strategy focuses on the concentration of urban population, specifically by encouraging the movement of urban residents from smaller cities to larger ones, while keeping the rural population constant. This strategy aims to harness the potential of larger cities to accommodate and sustain a greater population density, thereby further enhancing the super-linear scaling effect. However, the super-linear growth does not only mean the super-linear growth of wealth, innovation, and healthcare, but also leads to super-linear growth of undesired outcomes such as crime and spread of contagious diseases which are due to super-linear social interaction among people. Policymakers should pay special attention on those super-linearly growing unintended consequences to ensure the social cohesion and environmental sustainability.

The practical implications of our findings highlight the importance of understanding the limitation and possibility of country growth. These scaling relationships predict multiple dimensions of development a country can expect with respect to population change and urbanization. Such predictions help policymakers set realistic targets for development policy and develop strategies to address unintended consequences. These findings also provide a quantitative argument against mainstream practice of comparing national development using population-normalized measures,[2,3,6–10] which assumes development indicators scale linearly with population.[18,22] This assumption, however, does not always hold, since it ignores the effect of agglomeration resulting from non-linear interactions in social dynamics. New rankings of nations using scale-independent indicators provide new and more accurate comparison of the performance of national development (Methods and Table S5). For example, China's ranking by per-capita GDP in 2019 is improved from the 77th to the 53rd after scale-independent adjustment. In contrast, Mexico ranks higher than China based on per-capita GDP but lower after scale-independent adjustment. Such comparison indicates that, on a per-capita GDP basis, China in fact outperforms Mexico after considering the scaling effect of their populations.

Limitations of the study

While our study has yielded insights, there are certain limitations that should be improved in the future studies. Firstly, one limitation arises from the lack of prior evidence of scaling in rural systems, prompting us to assume linear scaling with some elasticity in our simulations. Future investigations should prioritize examining scaling relationships in rural systems, rather than solely focusing on urban areas. The advancements in remote sensing technologies[66,67] offer promising opportunities to address this by providing more detailed insights into rural economic activities and population distributions. By integrating such data sources, we can enhance the accuracy of estimations within rural systems and facilitate a more comprehensive understanding of scaling dynamics across diverse geographic contexts. Secondly, our study focuses to only a subset of national indicators due to limited data availability. Future research may leverage the state-of-art data science and machine learning approaches to enlarge the datasets[68,69] and continue generalizing the empirical observations of scaling to encompass a broader range of country-level properties. The deviation of various development indicators from the scaling is particularly important to understand how local characteristics play a role in country growth. Further exploration of scaling relationship at the country level will provide a unique perspective on how socioeconomic dynamics shape the development of a country and its impacts on energy, resources, and the environment. This insight might help identify pathways of sustainability transition toward open-ended growth and sustained improvement of human living standards within the planetary boundary.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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- RESOURCES AVAILABILITY
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  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Indicator selection
  - National scaling investigation
  - Scaling-adjusted inter-country comparison
  - Sensitivity test for robust results

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2024.110497.

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AUTHOR CONTRIBUTIONS

Study concept and design: C.S., C.L., and M.X.; analysis and interpretation of data: C.S., C.L., S.Q., X.C., B.Z., J.Z., and M.X.; drafting of the manuscript: C.S., C.L., and M.X. All authors have read and approved the final version of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
General development indicators	World Bank[49]	https://data.worldbank.org
Death related indicators	Our World in Data[50]	https://ourworldindata.org
Crime related indicators	United Nations[51]	https://dataunodc.un.org
Software and algorithms		
R studio	R studio	https://posit.co/download/rstudio-desktop/

RESOURCES AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Ming Xu (xu-ming@tsinghua.edu.cn).

Materials availability

This study did not generate new datasets.

Data and code availability

- This paper analyzes existing, publicly available data. These accession numbers for the datasets are listed in the key resources table.
- The R code generated in this study is available from the lead contact upon request.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Indicator selection

To ensure that our scaling results would hold universal and representative value for nations globally, we employ two specific criteria for selecting data samples, including data completeness and the relationship between dependent and independent variables. Firstly, we require that each year's data samples encompassed more than 100 countries, spanning various levels of development. This ensures that the scaling analysis covers a diverse and comprehensive representation of countries across the world. Secondly, we aim for a substantial explanatory power between the national population and the development indicators, measured by an adjusted R-squared value of more than 0.5. This criterion ensures that the national population have a considerable influence on the variation observed in the national development indicators. As a result of our data selection process, we are able to test the scaling effect for a total of 58 development indicators spanning the years 1995–2019.

National scaling investigation

The scaling of an indicator is expressed as follows[41,42]:

$$Y = Y_0 N^{\beta}$$

where Y indicates a certain indicator (e.g., GDP or employment) of a country, N is the total population of a country, Y_0 is a normalization constant, and β is the scale-invariant elasticity indicating the percentage change in Y following a 1% increase in N. If we take the log for both sides, the equation can be rewritten as follows:

$$\log Y = \log Y_0 + \beta \log N$$

It becomes a linear line in log-log scale where β represents the slope of the line. There can be three categories of β, namely super-linear with population ($\beta > 1$) which means countries with larger population tend to have even larger levels of these indicators on a per capita basis; linear with population ($\beta = 1$) which means countries with different population size tend to have similar per capita level of these indicators; and sub-linear with population ($\beta < 1$) which means countries with larger population tend to have smaller per capita levels.[53] We fit the data by using ordinary least squares (OLS) to find β.

Scaling-adjusted inter-country comparison

Some traditional population-normalized indicators in inter-country comparison (e.g., GDP per capita-based comparison) ignores the non-linear scaling effect of population on development indicators, which calls for a scale-independent indicator for fair and accurate comparison. The residual (ε) of each nation in the above scaling regression model could be considered as a distance between the general performance at the global level, which is used to re-rank the countries in terms of national scaling.[18,54]

$$\varepsilon = \log \frac{Y}{Y_0 N^{\beta}}$$

For the positive directional indicators like GDP, larger ε means better performance. For the negative directional indicators like CO_2 emissions, smaller ε means better performance.

Sensitivity test for robust results

We design three sensitivity tests for robust scaling. Firstly, we examine the potential impact of varying sample sizes in each development indicator on the scaling exponent. The data samples for most indicators encompass 130 to 190 nations, with a difference of approximately 30%. To address this, we conduct 1,000 random simulations by removing 30% of nations and retesting the scaling. Secondly, we investigate whether the scaling exponents were dominated by a few developing and less developed nations with large population. We test the impact of top three developing and less developed nations with large populations (i.e., China, India, and Nigeria) on the scaling exponents of each kind of indicator (i.e., GDP, incidence from tuberculosis, and employment). We conduct tests with two scenarios: one where the top three samples are removed, and another where the indicator performance is doubled or halved while keeping the population constant. Thirdly, we assume linear scaling (i.e., $\beta_r = 1$) in rural system due to lack of prior evidence and less active economic activities. We also test several ranges of β_r including [0.90, 1.00], [0.95, 1.00], [0.95, 1.05], [0.95, 1.05], [1.00, 1.05] and [1.00, 1.10].